Fast interactive medical image segmentation with weakly-supervised deep learning method

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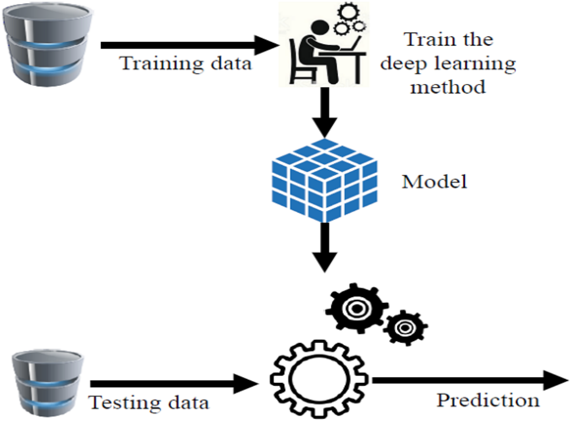
Medical image segmentation

- It is essential in various clinical applications
  - Medical image analysis
  - Clinical interventions
- Examples:
  - Measurement of area and volume of organs
  - Analysis of a large population of cases
  - Visualization in image-guided surgery

Promising approaches

- Deep learning methods

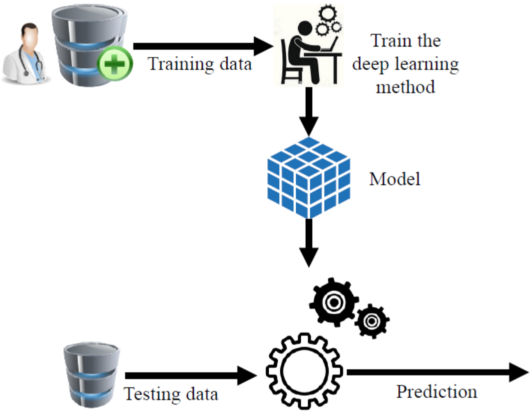


Challenges

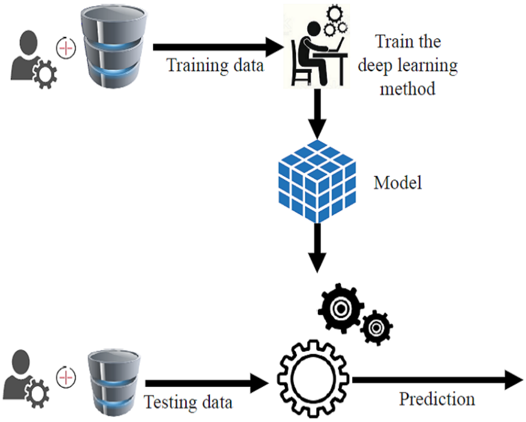
- Deep learning methods require large and diverse annotated dataset
- Annotated dataset are often limited because:
  - prone to variations in acquisition parameters
  - need high-level expert's knowledge
  - manually labeling targets by tracing their contour is often laborious
- Developed deep learning methods are likely to fail in some testing dataset when there is a slight difference from the training dataset (generalization problem)

ImViA

Possible solutions



A. Retraining from new cases



B. Minimal manual interaction

Possible solutions

- Retraining the developed deep learning method with new labeled cases
- Minimal manual interaction in conjunction with the deep learning methods to improve the accuracy

Developing an automatized deep learning method that allows experts to interact for better accuracy while increasing annotated dataset (smart annotation) would be beneficial.

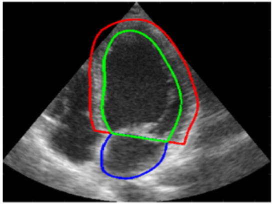
Dataset

- Prostate segmentation from CT and TRUS images
  - 78 CT exams
  - 145 TRUS exams
  - Difficult images to segment
  - Domain adaptation application
- Cardiac segmentation from ultrasound images
  - 450 2D echocardiography exams [1]
  - Multi-structure segmentation

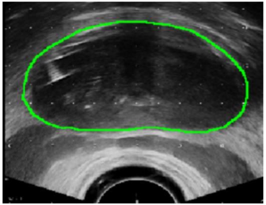
[1] Leclerc S, et. al. (2019), IEEE T MED IMAGING.

Pre-processing

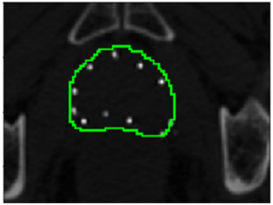
- TRUS and CT data are resized and cropped to $256 \text{ x } 256 \text{ x } 64$
- Cardiac images are resized to 256×256



Echocardiography

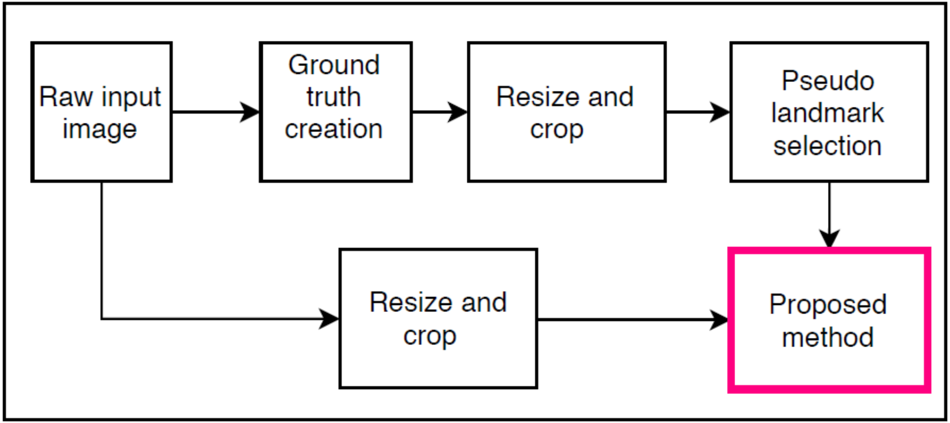


TRUS



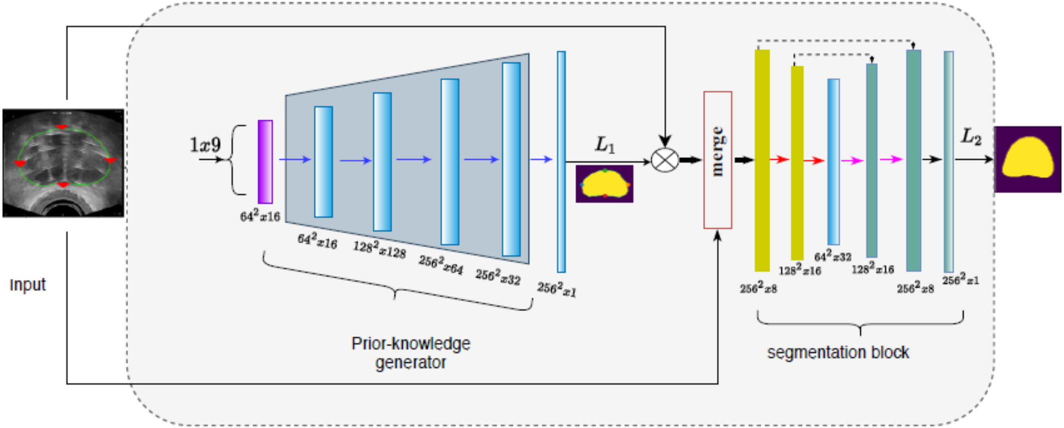
CT

Proposed framework



Proposed framework for the training

Method



Proposed end-to-end architecture.

Training loss function

$$L_{total} = \frac{1}{2} \times (L_1 + L_2) \quad (1)$$

- L_1 and L_2 are the sum of binary/categorical cross-entropy and Dice coefficient loss
- $L_i = L_{binary/categorical} + L_{dice},\ i = 1, 2$
- Training strategy:
  - Adam optimizer
  - Learning rate of 0.0001
  - Batch size of 20

Segmentation results on TRUS images

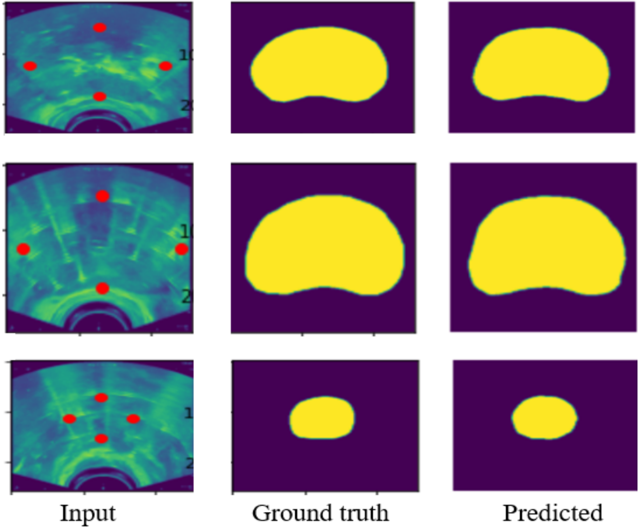


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Image	%	Metric			
		DSC (%)	HD (mm)	VO (%)	ACC (%)
TRUS	Total	96.9 ± 0.9	4.25 ± 4.6	93.9 ± 1.8	98.9 ± 0.5
	Middle	97.4 ± 0.6	3.28 ± 0.9	94.9 ± 1.1	98.1 ± 0.6
	Apex	96.4 ± 1.0	3.19 ± 1.1	93.1 ± 1.9	98.9 ± 0.4
	Base	96.5 ± 1.5	4.42 ± 4.6	93.4 ± 2.8	98.0 ± 1.1

DSC: Dice Similarity Coefficient
HD: Hausdorff distance
VO: Volume overlap ratio
ACC: Accuracy

Segmentation results on CT images

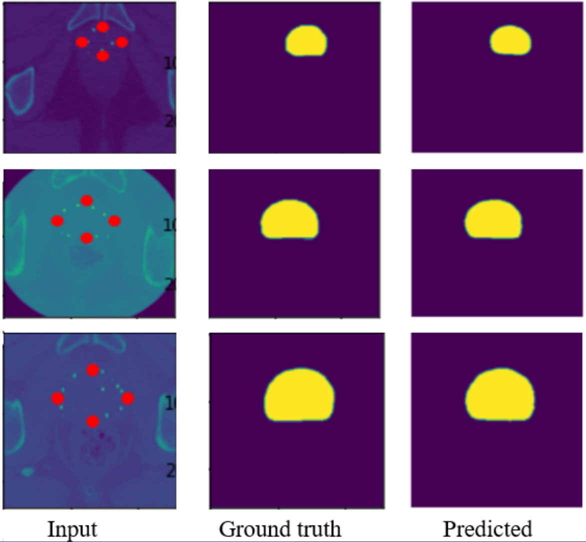

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Image	%	Metric			
		DSC (%)	HD (mm)	VO (%)	ACC (%)
CT	Total	95.4 $\pm$ 0.9	5.17 $\pm$ 1.4	91.3 $\pm$ 1.7	99.7$\pm$ 0.1
	Middle	95.9 $\pm$ 0.9	4.94 $\pm$ 1.6	92.2 $\pm$ 1.7	99.3 $\pm$ 0.3
	Apex	94.9 $\pm$ 1.8	3.56 $\pm$ 1.6	90.3 $\pm$ 3.2	99.6 $\pm$ 0.2
	Base	95.1 $\pm$ 1.2	4.92 $\pm$ 1.4	90.6 $\pm$ 2.2	99.3 $\pm$ 0.2

DSC: Dice Similarity Coefficient
HD: Hausdorff distance
VO: Volume overlap ratio
ACC: Accuracy

Segmentation results on echocardiography images

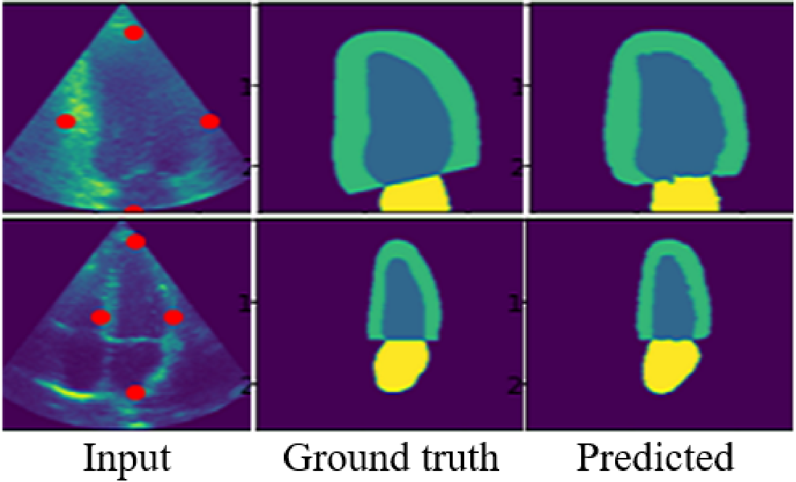

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Image	%	Metric DSC (%)	HD (mm)	VO (%)	ACC (%)
US	Total	96.3 ± 1.3	23.0 ± 10.4	93.3 ± 0.0	98.6 ± 0.0
	LV	93.2 ± 4.9	14.2 ± 5.7	87.2 ± 7.5	98.8 ± 0.0
	LA	91.9 ± 6.6	14.9 ± 5.7	84.9 ± 0.1	99.1 ± 0.0
	MYO	89.5 ± 11.9	22.4 ± 21.1	81.0 ± 0.1	98.0 ± 0.0

DSC: Dice Similarity Coefficient; HD: Hausdorff distance (in mm)
VO: Volume overlap ratio; ACC: Accuracy
LV: Left ventricle, MYO: Myocardium; LA: left atrium

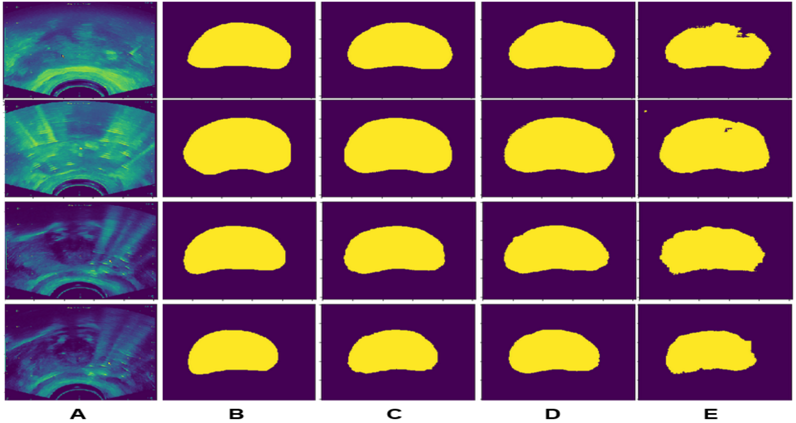
Ablation study

- Ablation study of the merging block using TRUS images
  - Concatenation (Concat.): providing both images as input
  - Addition (Add.): pixel-wise intensity addition
  - Multiplication (Mult.): pixel-wise intensity multiplication

Metric	Concat.	Add.	Mult.
DSC (%)	96.9 ± 0.90	95.9 ± 0.68	96.8 ± 0.67
HD (mm)	4.25 ± 4.58	15.95 ± 8.65	4.94 ± 3.58
VO (%)	93.9 ± 1.80	92.2 ± 1.25	93.8 ± 1.29
ACC (%)	98.9 ± 0.50	98.6 ± 0.44	98.9 ± 0.37

DSC: Dice Similarity Coefficient, HD: Hausdorff distance
VO: Volume overlap ratio, ACC: Accuracy

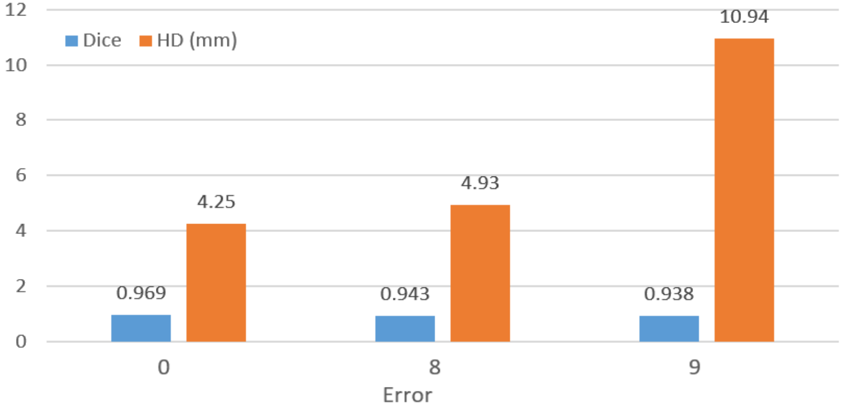
Segmentation results



(A) original input image, (B) ground truth labels, (C) concatenation, (D) multiplication, and (E) addition

Inter and intraobserver variational studies

- Introduced errors on the selected landmarks for TRUS segmentation



[4] Sandhu GK. et al. 2012 INT J RADIAT ONCOL

Domain adaptation study

- A trained model on a given dataset can be applied to different domains but for a similar target (called domain adaptation)
- Trained model from TRUS images is applied on CT image segmentation by retraining using only 20 CT cases and vice versa, named weakly-supervised
- Trained model on TRUS dataset is directly applied on testing CT images and vice versa, named unsupervised.

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Training	Testing	Metric	Weakly-sup. Conc.	Unsupervised Conc.	Unsupervised Mult.
TRUS	CT	DSC (%)	94.8 ± 1.7	87.8 ± 6.4	89.1 ± 5.0
		HD (mm)	5.68 ± 2.1	22.9 ± 28.9	10.1 ± 4.3
		VO (%)	90.2 ± 3.0	78.9 ± 9.7	80.7 ± 7.6
		ACC (%)	99.6 ± 0.1	99.1 ± 0.6	99.2 ± 0.4
CT	TRUS	DSC (%)	96.5 ± 0.8	84.7 ± 4.1	84.3 ± 4.0
		HD (mm)	5.20 ± 2.9	28.4 ± 7.9	20.7 ± 6.9
		VO (%)	93.2 ± 1.5	73.6 ± 6.1	73.1 ± 6.0
		ACC (%)	98.8 ± 0.4	95.0 ± 2.0	95.0 ± 2.0

DSC: Dice Similarity Coefficient, HD: Hausdorff distance
VO: Volume overlap ratio, ACC: Accuracy
Conc.:Concatenation, Mult.: Multiplication

Summary

- We proposed an efficient and interactive method for accurate and robust medical image segmentation
- It can be used to transfer prior-knowledge of clinical targets between different imaging modalities
- Fast, interactive deep learning methods have the potential to solve the bottleneck of deep learning methods in the adaptation of clinical center variations
- In future work, we will investigate how to reduce the number of pseudo landmarks, e.g., consider the 3D data

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